# AGENT-BASED ANALYSIS OF COMPETITIVE SAV OPERATIONS: VARIABLE PRICING AND MULTI-SERVICE STRATEGIES

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## ABSTRACT

This study examined shared autonomous vehicle (SAV) fleet performance with service-specific variable fares in a competitive ride-hailing market. It calibrates operator-specific fare models using New York's ride-hailing dataset, enabling fare adjustments based on demand fluctuations, and the hour of the day. Agent-based POLARIS simulations of two SAV operators (Operator 1 and Operator 2) in Bloomington city, showed that a variable fare strategy allows operators to swiftly adjust to demand variations improving fleet usage and turned underperforming fixed-fare services into profit centers. Under fixed fares, results suggest that operators had to "pick a winner": Operator 1 stayed profitable (with 51% profit margin) by focusing on 4-seaters, while Operator 2's mixed-fleet strategy incurred steep losses in premium tiers ($66 daily loss per 4-seater premium SAV and $278 daily loss per 6-seater premium SAV) yielding just 2% overall profit margin. In contrast, variable pricing generated dramatic economic and efficiency gains with a 174% rise in total profit, more than tripling daily profit per SAV from $107 to $348 (after reducing total fleet size from 455 to 385 SAVs). Since demand fell 14.5%, SAV fleet VMT fell 17%, and the share of

empty VMT fell from 32% to 25%. This operational efficiency was most evident for Operator 2, whose average vehicle occupancy (AVO) jumped 19% (from 1.32 to 1.55 occupants per revenue-mile, assuming 1-person travel-party size.

**Keywords:** Variable pricing, Shared autonomous vehicles (SAVs), Ride-hailing competition, Surge pricing.

## BACKGROUND

SAV markets remove the driver decision layer altogether, enabling operators to focus purely on fleet sizing, dynamic fare strategies, and demand management (Zhang, 2023; Fagnant and Kockelman, 2014 and 2015; Levin et al., 2017). Early commercial deployments of SAV fleets in San Francisco's Bay area highlight this technology's promise and regulatory fragility (SFCTA, 2024; Waymo, 2023). As multiple operators, including Cruise, Waymo and Zoox, compete for market share, examining fleet sizing, service differentiation, and market entry sequencing is essential to predict which business models will thrive and how pricing competition will influence overall system efficiency and coverage (Marshall, 2018; Sambasivam et al., 2024; Fakhrmoosavi et al., 2023). These operators not just compete with each other but will also compete with traditional TNCs (Uber and Lyft). They will compete just like today's TNCs, with providers strategizing their fares and services to capture larger market share while competing in local markets. For instance, Didi and Uber China were engaged in a price war until 2016, but by November 2023, Uber had regained a portion of its lost market share, stabilizing the competitive dynamics between the two companies. Currently, Uber and Lyft compete in the U.S., while Grab and Gojek compete in Southeast Asia, Ola and Uber in India, Bolt and Uber in Europe, and Careem and Uber in the Middle East (Wang and Yang, 2019). Didi also faces competition from Chinese rivals, like Shouqi, Meituan, and Shenzhou (Zhou et al., 2022).

Past studies have used agent-based simulation approaches to analyze the competitive ride-hailing market. Mo et al. (2021) used an agent-based simulation model (ABM) to explore the competition between SAVs and public transit (PT) in Singapore, finding that SAVs could capture up to 30% of the PT market share in low-density areas where PT services are less efficient. Karamanis et al. (2020) also used ABM and compared dynamic pricing's effects on monopolistic and competitive SAV fleet scenarios in Greater London, finding that dynamic pricing led to higher revenues than static pricing during non-peak hours in monopoly settings, while in competitive scenarios, dynamic pricing was more effective during peak hours due to high waiting times. Guo et al. (2022) developed a comprehensive optimization framework for SAVs competing with human-driven private vehicles by integrating a binary logit demand model with a time–space network-flow formulation. Their Singapore BlueSG network case study showed that when demand is low, higher sensitivity boosts profit. Still, when demand is high, it can actually reduce profit by over-investing in service quality. They found that optimal fleet sizing balances utilization and service, resulting in roughly 5-6 requests per vehicle during peak hours, which maintains over 80% fulfillment without excessive idle time. Sambasivam et al. (2024) revealed counterintuitive service insights under competitive configurations. Under identical dynamic pricing, the smaller fleet often posts shorter peak-hour wait times by concentrating vehicles in high-demand zones, though larger fleets typically promise faster pickups under flat fares. They found that SAVs' extended operational hours, 11-12 hours daily versus the 8-9-hour limits of human-driven TNCs, amplify revenue potential, especially under dynamic fare strategies exploiting both temporal and spatial demand peaks.

However, as SAV operations scale in the future, negative externalities are likely to emerge, including intensified congestion, increased deadheading (empty miles), and overlapping fleets that crowd busy routes or divert riders from efficient transit. These issues have increased regulatory scrutiny (Henao and Marshall, 2019; Schaller, 2021), prompting policymakers to devise rules for both ride-hailing (Li et al., 2022; Zhang and Nie, 2019) and AV fleets. Simoni et al. (2019) evaluated congestion-pricing schemes in the presence of SAVs, Dandl et al. (2021) embedded ride-pooling constraints within a tri-level optimization of tolls, parking fees, transit frequency, and fleet caps, while Mo et al. (2021) explored how fleet-size limits and transit subsidies shift equilibria over day-to-month operator responses. Amidst these competitive global trends in the ride-hailing market, several studies have assessed local operational effectiveness and competitive interactions among these operators/service providers (Paronda et al. 2016; Huang et al. 2023; Meskar et al. 2023) but overlooked the feedback relationship between provider fares and (instantaneous) service demands1. Ideally, dynamic fares should respond not only to instantaneous supply–demand imbalances, but also to lagged demand spillovers. Sambasivam et al., 2024 effectively captured broad effects of pricing structures but failed to predict how truly profit-maximizing operators would adjust fares in response to continuously evolving demand, competitor behavior, and rider acceptance thresholds. Moreover, by pre-specifying each operator's TOD and ZSP multipliers, existing simulations sidestep the critical topic of endogenous price effects.

In practice, dynamic-pricing systems continuously calibrate surge levels using optimization routines that account for real-time ridership patterns, competitor fares, and marginal profit contributions. Without modeling this feedback loop, static-multiplier analyses risk overstating or understating the revenue and operational impacts of fare strategies under true market conditions. Similarly, limiting ride-type offerings to a single "standard" SAV option with a binary pooling discount fails to reflect the multi-tiered service portfolios (economy, premium, pooled, and subscription plans) that competing platforms offer to capture diverse customer segments. To address these gaps, this study extends the SAV duopoly market literature by implementing time-varying, ride-option–specific pricing algorithms calibrated on NYC-TLC data. Rather than applying fixed multipliers, the study estimated continuous fare-elasticity functions for each ride option and allowed fares to adjust hour-by-hour based on current demand, and competitor fare changes. This empirically grounded approach captures the true dynamics of variable pricing by modeling how operators would optimally respond to both immediate supply–demand imbalances and lagged demand spillovers. The remainder of this paper is organized as follows. The next section details the POLARIS simulation network framework for multi-operator, multi-service scenarios. The subsequent section presents operator-specific fare strategies and their implementation. The fourth section presents and discusses simulation results examining the operational and economic performance of these scenarios. Finally, the paper concludes with a summary of key findings and their policy implications for the emerging SAV market.

## AGENT-BASED SAV SIMULATION FRAMEWORK

This study is based on Argonne National Laboratory's POLARIS code, which enables microsimulation of SAV operations with and without DRS (Auld et al., 2016; Gurumurthy et al., 2020). POLARIS is an advanced, open-source, agent-based modeling framework designed to simulate multi-modal transportation systems at a mesoscopic level, with a separate agent for every member of the regional population (100% agents). It integrates travel demand, network flow, and traffic assignment models, allowing travel decisions, such as activity planning and route choice, to be modeled simultaneously. The activity models, adapted from Auld and Mohammadian (2009 aand 2012), model each traveler's decision-making process across short-term and long-term timeframes, considering activity types, destinations, and preferred modes. The travel demand simulator can perform comprehensive simulations due to its integration of a population synthesizer that can iteratively adjust the agent population averages across various categories to align them with the regional cross-tables. The synthesizer enables the efficient scaling of simulated individual agents, while POLARIS is high-speed C++ code capable of simulating nearly all regions' populations with great efficiency. Using dynamic traffic assignment (Verbas et al., 2018), network traffic is balanced to achieve a dynamic user equilibrium.

POLARIS employs a traditional modeling approach to separate mode-choice models based on different activity purposes: home-based work/school, home-based other, and non-home-based. Each choice is modeled using a nested-logit model, which includes nine transportation modes: driving alone, using TNC services, riding as a passenger, walking, biking, bus with walk access, bus with drive access, rail with walk access, and rail with drive access. In this model, driving alone and TNC are grouped under the "auto" branch (Figure 1), while the two rail modes are grouped under the "rail" branch. Various demographic factors, accessibility data, and level of service (LOS) factors are included in the model. The demographic factors include individual characteristics like education level, employment status, and whether a person holds a driver's license, as well as household information such as income, household size, and vehicle and bike ownership. The model also includes factors such as land-use characteristics and the transportation network by using road-network density and activity density in the destination zone. For analysis, the LOS variables include in-vehicle travel time, wait time, and fare, where wait time is calculated from simulation runs and fares are inputs to the model.

## METHODOLOGY

SAV simulations have used POLARIS previously (Dean et al., 2021; Huang and Verbas, 2021; Gurumurthy et al., 2022; Hunter et al., 2024), and a single SAV operator is responsible for the centralized management of ride requests and may reposition SAVs in response to changes in vehicle demand-supply ratios. The SAV operator performs repositioning tasks while maintaining a record of present and potential execution requests. The model addresses the needs of travelers who opt for ride-sharing using the DRS algorithm, which includes a heuristic approach to effectively handle travel delays encountered at various points during the trip, as discussed by Gurumurthy and Kockelman (2022a and 2022b). When an SAV trip request is logged, the operator assigns it to the nearest vehicle to reduce eVMT and wait time in a zone-based structure. This study extends the ride-option choice framework developed by Paithankar et al., 2024 for a single SAV operator to a two-operator scenario. At the upper level, travelers select SAV over other modes using a multinomial logit model based on network skims of travel time, wait time, and fare estimates (Figure 1). At the lower level, riders who opt for SAV compare the two operators based on predicted fares and trip durations. Rather than imposing fixed time-of-day or zone-based fare multipliers, each operator employs a ride-option-specific fare-prediction regression model. Estimated on NYC TLC data, this model forecasts the rider fare for each trip and ride type (economy 4-seater, economy 6-seater, premium 4-seater, premium 6-seater) as a function of distance, duration, instantaneous demand, past demand (demand ratio), and hour of day. The regression-based pricing engine runs continuously: at every simulation run, each operator updates its fare predictions for each service option based on current demand densities and prior-period spillovers. These endogenously generated fares then feed back into both the operator-choice and service-choice utilities, capturing how profit-maximizing algorithms would calibrate prices in a competitive market.

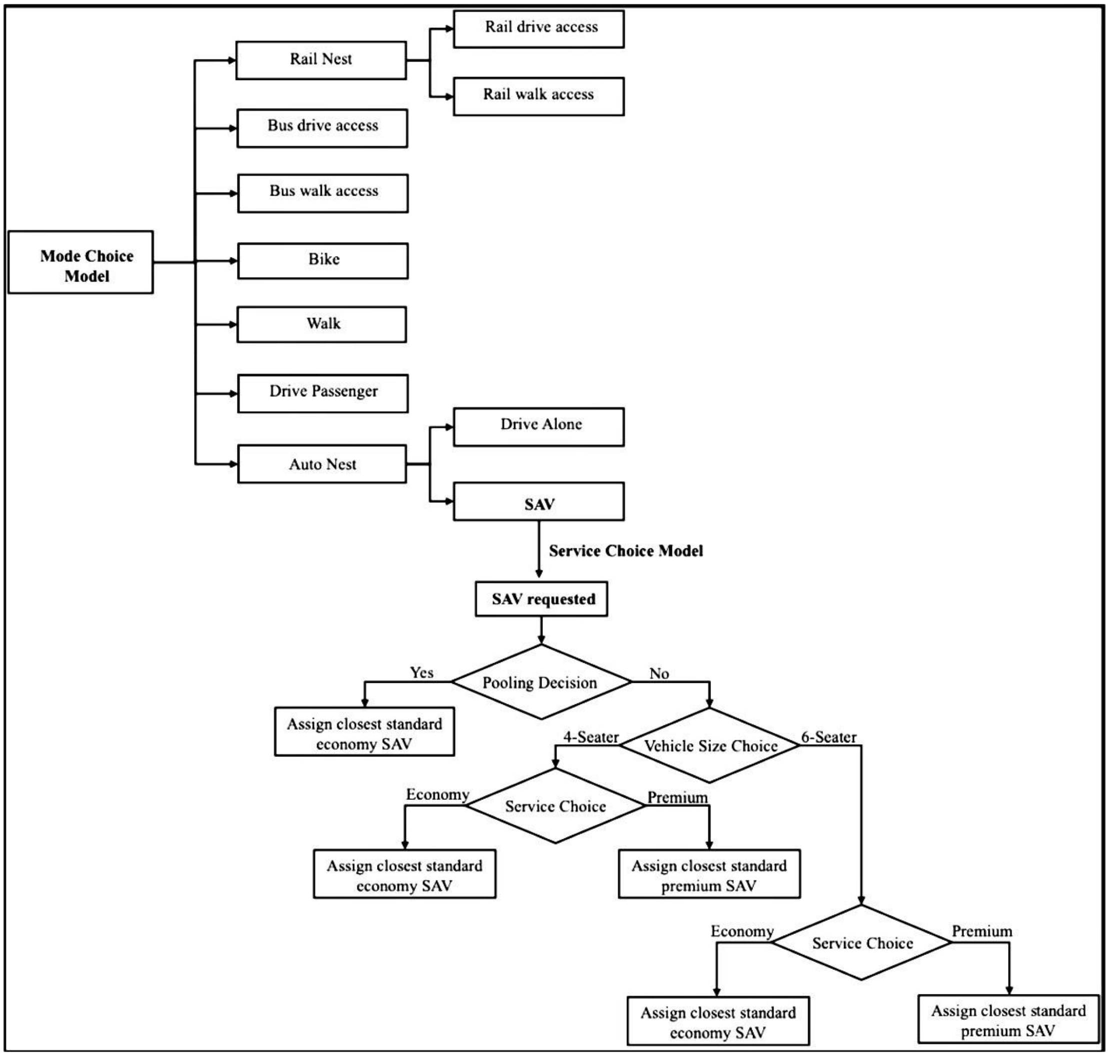


**Figure 1 Mode Choice Model with Integrated Service Choice Framework (Paithankar et. al., 2025)**

Once a rider has selected both an operator and ride option type, the vehicle-assignment logic executes in real time (see Figure 2). First, the system checks whether the trip request is for a future reservation or an immediate pickup: future reservations are added to a reservation queue, while immediate requests proceed directly to the matching module. In the matching phase, each operator's SAV fleet is scanned, identifying SAVs who are currently idling or in a repositioning status. For each SAV, the simulation verifies (1) that the vehicle's current onboard load plus the new party size does not exceed its seating capacity and (2) that assigning the party would not violate any DRS rules (for example, total delay stays within acceptable limits). If both conditions hold (i.e., capacity is sufficient and DRS constraints are satisfied), the vehicle is assigned to the request, and a pickup time is scheduled for its next available slot. If either check fails, the search continues through the remaining idle/repositioning SAVs until a feasible match is found (or until the request is turned down if no suitable SAV becomes available).

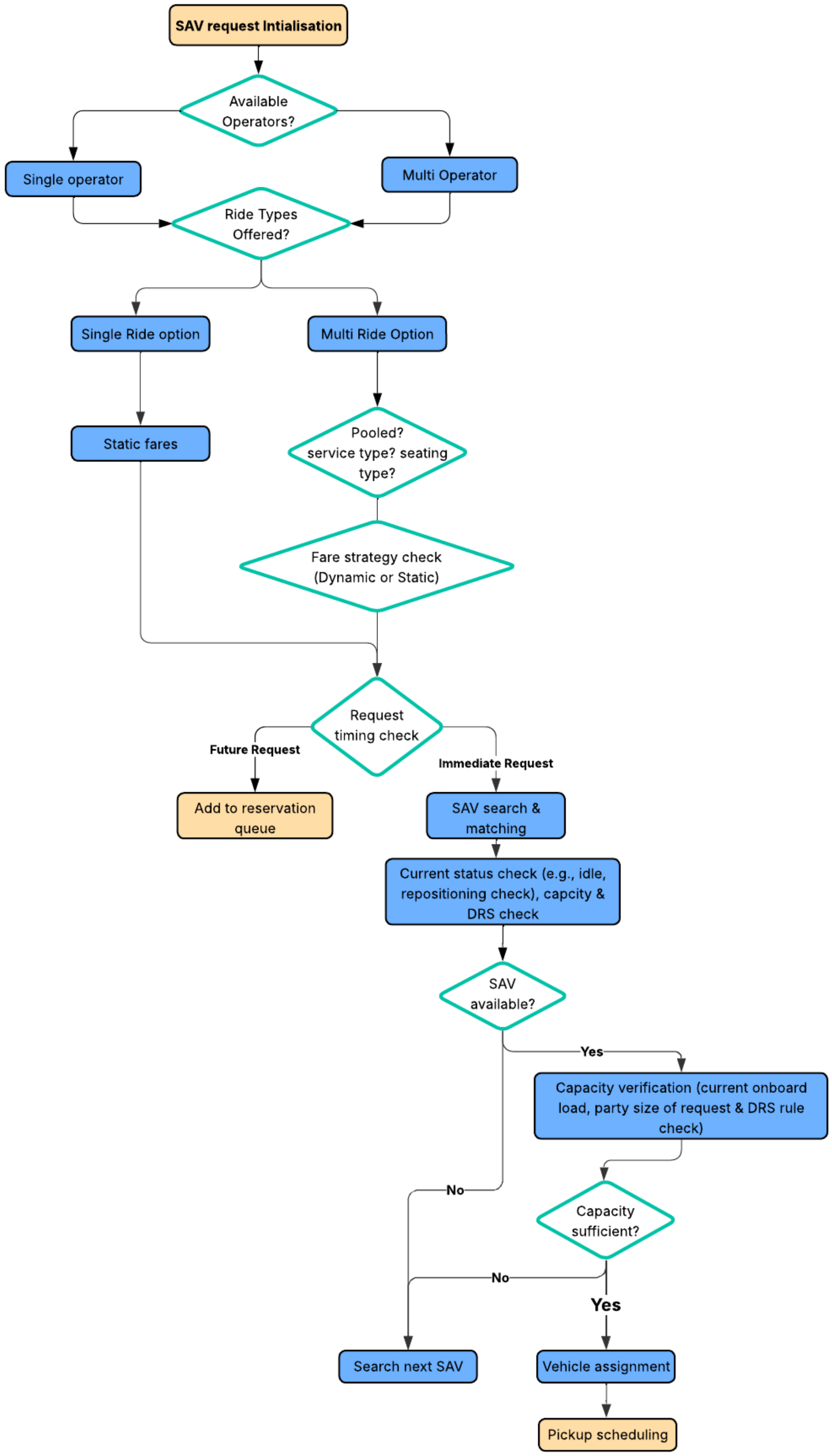


**Figure 2 Flowchart of SAV Request Processing and Vehicle Assignment Logic in POLARIS**

## OPERATOR-SPECIFIC VARAIABLE FARE STRATEGY

In NYC's crowded ride-hailing market, Uber and Lyft have both adopted tiered fare structures, but they emphasize different levers to maximize revenue and manage fleet usage. This study has leveraged detailed ride-hailing trip data from NYC (TLC Trip Record Data, 2023) across all five boroughs (Bronx, Brooklyn, Manhattan, Queens, and Staten Island) and Newark Airport. The data includes trip records from medallion-regulated yellow and green taxis alongside app-based for-hire services; however, our analysis is confined to the Uber and Lyft subsets, comprising approximately 9.8 million rides between September 15 and September 30, 2024. These trips represent roughly 65–70% of the total for-hire vehicle market in NYC. The variations of 2024 ride-hailing volumes over a year reveal a gradual upward trend in average daily trips for Uber and Lyft, rising from about 630,000 in January 2024 to approximately 680,000 in December 2024. Seasonal demand intensifies during the October–December window, likely driven by holiday travel and year-end social activity. The highest daily average observed since January 2021 occurred in March 2024, at approximately 690,000 trips per day. September was selected as a reference period because it reflects normative urban mobility conditions, schools are fully in session, workplaces operate at normal capacity, COVID-19 impacts have significantly diminished, and extreme weather conditions are generally absent.

Table 1 provides summary statistics of all variables available in this dataset. Uber dominates NYC's ride-hailing market, with approximately 72% of all trips analyzed (compared to Lyft's 28%). The ride-sharing requests are relatively low, with only about 3.07% of all trips involving riders requesting this service and an even smaller fraction (0.99%) resulting in a matched ride. Approximately 41% of trips incurred a congestion surcharge ($2.75 per trip), indicating that these rides began and ended in New York State and either originated, concluded, or passed through Manhattan south of 96th Street, while 24% of trips either originated, concluded, or passed through new congestion zone, which extends from 60th Street down to Battery Park and will now pay additional $1.5 per trip as per NYC's congestion pricing program launched on January 5, 2025 (NYC TLC, 2024). In addition to these congestion fees, riders are subject to a $2.50 Airport Fee for airport-related trips, an 8.875% sales tax, and a 2.75% Black Car fund fee, which contributes to driver benefits and safety programs (Lyft Blog, 2025).

Table 2 below summarizes the OLS fare-prediction regression results using NYC TLC trip data during September 2024 (with 19.8 million ride observations, of which 15 million are Uber trips and 4.8 million are Lyft trips). In Uber's fare regression model ($R^2 = 0.868$), the intercept of $2.52 represents the estimated base fare (in dollars) when trip distance, duration, and other covariates are zero. The distance coefficient (0.958) implies that each additional mile adds about $0.96 to the fare, while each additional minute contributes about $0.49. Shared-ride trips receive substantial per-unit discounts: pooled services on average of 58% lower per-minute charges and 20% per-mile charges. Weekend trips are associated with 13% lower fares, everything else constant. Uber offers lower marginal per-mile rates for larger or premium vehicles but adds extra time-based fees, rewarding passengers for longer trips in bigger cars, and Uber still earns a premium for vehicle availability (due to a larger fleet of drivers, and brand familiarity). The 6-seater economy tier (UberXL) reduces the per-mile fare coefficeint by about 32% (dropping from $0.958 to $0.656) while nearly tripling the marginal per-minute coefficient. An additional minute in UberXL is estimated to cost $1.447 versus $0.489 in UberX (on average), a 196% premium which suggest that riders will pay less per marginal mile but significantly more per added minute. In the case of Uber's 4-seat luxury cars (offered as UberBlack), the estimated marginal per-mile fee is $0.734 but the per-minute fare rises 288% (to $1.896).

**Table 1 Summary Statistics of NYC's Uber + Lyft Trips from September 15 to 30, 2025 (n = 9,875,667 ride-hailed trips)**

| Variable Name | Mean | Std. Dev | Min | Median (50%) | Max |
|---|---|---|---|---|---|
| Trip Distance (miles) | 2.87 mi | 5.93 | 0.00 | 2.21 | 10.9 |
| Trip Duration (minutes) | 18.4 min | 10.98 | 0.00 | 15.8 | 52.1 |
| Passenger Wait Time per Trip (min) | 4.66 min | 2.24 | 0.00 | 4.25 | 11.3 |
| Fare Paid per Trip ($) | $16.19 | 7.32 | 0.00 | 14.5 | 43.6 |
| Uber's Fare ($ per mile) | $6.35 | 2.60 | 0.03 | 6.10 | 15.6 |
| Lyft's Fare ($ per mile) | $8.07 | 3.03 | 0.01 | 6.50 | 15.6 |
| Tolls Paid per Trip ($) | $0.72 | 2.65 | 0.00 | 0.00 | 66.6 |
| Black Car Fund per Trip ($) | $0.46 | 0.22 | 0.00 | 0.42 | 1.16 |
| Sales per Tax per Trip ($) | $1.43 | 0.65 | 0.00 | 1.28 | 3.43 |
| Congestion Surcharge per Trip ($) | $0.93 | 1.30 | 0.00 | 0.00 | 5.50 |
| Airport Fee per Trip ($) | $0.19 | 0.67 | 0.00 | 0.00 | 7.50 |
| Tips Paid per Trip ($) | $1.01 | 2.72 | 0.00 | 0.00 | 100 |
| Driver's Pay per Trip ($) | $13.7 | 6.18 | 0.00 | 11.3 | 30.9 |
| Monday Trips (Indicator) | 0.12 | 0.32 | 0.00 | 00.0 | 1.00 |
| Tuesday Trips (Indicator) | 0.12 | 0.32 | 0.00 | 0.00 | 1.00 |
| Wednesday Trips (Indicator) | 0.12 | 0.33 | 0.00 | 0.00 | 1.00 |
| Thursday Trips (Indicator) | 0.13 | 0.34 | 0.00 | 0.00 | 1.00 |
| Friday Trips (Indicator) | 0.21 | 0.41 | 0.00 | 0.00 | 1.00 |
| Saturday Trips (Indicator) | 0.17 | 0.37 | 0.00 | 0.00 | 1.00 |
| Sunday Trips (Indicator) | 0.14 | 0.34 | 0.00 | 0.00 | 1.00 |

The Lyft model ($R^2 = 0.936$) begins with a lower intercept of $1.85, with Lyft's marginal per-mile charge ($1.568 per mile) being higher than its marginal per-minute rate ($0.367 per minute), indicating that Lyft leans more heavily on distance-based pricing. Each upgrade then adds a clear premium in both distance and time charges. The 6-seaters ride ("Lyft XL") adds modest per-unit additions of about a 21% raise over standard in per mile charge and a 65% increase in marginal per minute charge ($0.33 per mile, $0.24 per minute), and luxury offerings raise marginal per-mile costs ($0.64 for 4-seat, $1.72 for 6-seat) alongside moderate time premiums ($0.48, $0.89). In case of luxury offerings, the 4-seat option boosts per-mile fees by $0.64 (a 41% bump) and marginal per-minute fees by $0.48 (a 132% jump). The most expensive option is the 6-seater luxury ride, which incurs an additional $1.72 per mile (110% above economy) and $0.89 per minute (241% above economy). Thus, when riders choose the largest luxury vehicle, they pay more than twice as much per mile and nearly four times as much per minute compared to the base service.

Uber and Lyft take fundamentally different approaches to time-of-day pricing in NYC. Uber's fare adjustments are highly variable, with sharp surges when demand peaks, steep discounts when demand reduces, and continuous minute-by-minute tweaks. This contrasts with Lyft, which adds modest premiums around peak commute windows and holds fares largely flat the rest of the day. This difference stands out most sharply during the overnight and early morning hours. Between 1 AM and 5 AM, Uber imposes substantial markups, peaking at $0.90 per minute around 4 AM to attract drivers into low-supply shifts. Lyft, by comparison, shows almost no overnight variation, signaling a "steady hands" strategy that trades big gains for consistent gains. At 8 AM, Uber offers a $0.03/minute discount to ease the morning rush, while Lyft adds $0.17/minute for its standard commute premium. During 11 AM–3 PM and again from 5 to 8 PM, Uber's surcharges sit around $0.14–$0.17/minute, dip after lunch, and fall to $0.39 by 8 PM, while Lyft's rates climb to $0.51/minute at 3 PM and hold at $0.25 from 4–7 PM. Lyft, in contrast, steadily increases fares into the afternoon (up to $0.51/minute at 3 PM) and then applies a consistent $0.25 uplift during 4 to 7 PM.

**Table 2 OLS Fare-Prediction Regression Coefficients for Uber and Lyft Services (Y Fare per trip in dollars, N = 19 million rides)**

| | **Y = Uber's Fare per trip ($)** | **Y = Lyft's Fare per trip ($)** |
|---|---|---|
| | **N= 15 million trips, $R^2$=0.868** | **N= 4.8 million trips, $R^2$=0.936** |
| **Variable Name** | **Coefficient** | **Coefficient** |
| Base Fare (Intercept) | 2.524 | 1.849 |
| Trip Distance Rate ($/mile) | 0.958 | 1.568 |
| Trip Time Rate ($/minute) | 0.489 | 0.367 |
| Shared-Ride Time Discount ($/minute) | -0.286 | - |
| Shared-Ride Distance Discount ($/mile) | -0.189 | - |
| Weekend trip? | -0.518 | -0.215 |
| Demand Ratio Surcharge ($ per unit) | 0.088 | - |
| 6-Seater Economy Distance Adjustment ($/mile) | -0.302 | 0.331 |
| 6-Seater Economy Time Adjustment ($/minute) | 0.958 | 0.240 |
| 4-Seater Luxury Distance Adjustment ($/mile) | -0.224 | 0.638 |
| 4-Seater Luxury Time Adjustment ($/minute) | 1.407 | 0.483 |
| 6-Seater Luxury Distance Adjustment ($/mile) | -0.380 | 1.724 |
| 6-Seater Luxury Time Adjustment ($/minute) | 2.735 | 0.886 |
| Hour 1 AM–2 AM Trip? | 0.351 | - |
| Hour 2 AM–3 AM Trip? | 0.530 | - |
| Hour 3 AM–4 AM Trip? | 0.627 | 0.030 |
| Hour 4 AM–5 AM Trip? | 0.900 | 0.040 |
| Hour 5 AM–6 AM Trip? | 0.616 | - |
| Hour 8 AM–9 AM Trip? | -0.034 | 0.169 |
| Hour 10 AM–11 AM Trip? | 0.170 | - |
| Hour 11 AM–12 PM Trip? | 0.165 | 0.210 |
| Hour 12 PM–1 PM Trip? | 0.138 | 0.318 |
| Hour 1 PM–2 PM Trip? | 0.021 | 0.319 |
| Hour 2 PM–3 PM Trip? | -0.075 | 0.410 |
| Hour 3 PM–4 PM Trip? | -0.056 | 0.510 |
| Hour 4 PM–5 PM Trip? | -0.212 | 0.510 |

| | | |
|---|---|---|
| Hour 5 PM–6 PM Trip? | -0.001 | 0.510 |
| Hour 6 PM–7 PM Trip? | 0.235 | 0.510 |
| Hour 7 PM–8 PM Trip? | -0.129 | - |
| Hour 8 PM–9 PM Trip? | -0.394 | 0.250 |
| Hour 9 PM–10 PM Trip? | -0.063 | 0.138 |
| Hour 10 PM–11 PM Trip? | 0.079 | 0.197 |
| Hour 11 PM–12 AM Trip? | 0.216 | 0.217 |

## SAV DEMAND UNDER MULTI-OPERATOR AND RIDE OPTION SCENARIO

Both operators assume a 4-seater standard SAV ownership cost of $40 per day plus $1.00 per mile; XL economy SAVs incur $60 per day plus $1.50 per mile, and premium (luxury) SAVs incur twice these operating costs. Previous studies have typically bundled cleaning and maintenance costs for SAVs into broader operational cost estimates (Loeb and Kockelman, 2019). They assumed a combined maintenance and cleaning cost of approximately $0.054–$0.066 per mile for privately owned vehicles. While Litman (2025) has suggested that cleaning costs could range from $0.33 to $2.00 per trip, depending on cleaning frequency and local labor rates, with these costs sometimes excluded from per-mile operating estimates. In this analysis, both operators assume a 4-seater standard SAV ownership cost of $40 per day plus $1.00 per mile; XL economy SAVs incur $60 per day plus $1.50 per mile, and premium (luxury) SAVs incur twice these operating costs. To account for cleaning, this study further assumes a cleaning cost of $1.50 per trip, which is added to the operational expenses for each trip completed by the fleet.

***Temporal Patterns in Median Wait Times under Fixed and Variable Fare Strategies***

Figure 4 shows how median passenger wait times vary over 24 hours under the variable fare strategy for both operators' 4 and 6-seat economy and premium rides. In the pre-dawn interval (1–4 AM), waits are minimal, typically between 2 and 4.5 minutes. As demand increases toward the morning commute hours (7–10 AM), all 4-seated services rise, but Operator 2's 4-seat economy peaks most sharply at nearly 17 minutes wait time by 8 AM. At the same hour, Operator 1's 4-seat economy and Operator 2's 4-seat premium services climb to 6.3 and 8 minutes, respectively, while Operator 2's 6-seat economy and premium peak around 7.5 and 6.5 minutes. Following the morning surge, wait times narrow to a midday plateau of 1.5 to 3 minutes between 11 AM–3 PM for all services except Operator 2's 6-seater economy service. This service-maintained wait times of 6.5 to 8 minutes throughout the day after 6 AM. A secondary, more modest wait time surge emerges in the evening (5–9 PM), when Operator 1's 4-seat economy returns to 6–7 minutes and Operator 2's 4-seat economy peaks at 8 minutes, while premium waits varies between to 1.5–4.5 minutes. Operator 1's 6-seat offerings remained inactive throughout due to the absence of demand.

Fixed fares resulted in two distinct rush-hour surges in wait times, accompanied by a broad midday plateau (Figure 5). During the early morning interval (1–3 AM), wait times for 4-seat economy and premium services were modest, at approximately 2 minutes. A pronounced commuter peak followed at 8–9 AM, when Operator 1's 4-seat economy and premium SAVs reached median wait times of approximately 7–8 minutes, and Operator 2's economy services both peaked at 4.8 minutes for 4-seaters and 7.5 minutes for 6-seaters. Thereafter, from late morning through mid-afternoon (10 AM – 5 PM), all active services reached a stable plateau of roughly 2–3 minutes. Operator 1's 6-seat offerings remained inactive throughout due to the absence of demand, while Operator 2's 6-seat fleet showed consistently higher wait times (compared to 4-seaters) at all hours. A secondary evening peak (5–7 PM) again raised Operator 1's 4-seat economy and Operator 2's

4-seat premium service' wait times to 7 minutes, before service's wait times declined toward 3 minutes after 10 PM. Under the variable-fare regime, the most price-sensitive segment, Operator 2's 4-seat economy actually endures a much sharper morning peak (nearly 17 min at 8 AM) than under fixed fares (≈ 4.8 min). At the same time, mid-day and off-peak waits for economy and premium services collapse to 1.5–3 min, versus a slightly higher 2–3 min plateau under fixed pricing. In contrast, fixed fares produce more uniform rush-hour peaks of 7–8 min across all active services and maintain a broad, moderate midday plateau, without any extreme spikes. Thus, varible pricing amplifies delays for the least price-elastic (high-demand) economy rides while compressing waits for premium and larger-seat services. This suggests that fare elasticity drives a redistribution of service: intense congestion (long waits) is confined to a narrow, inelastic segment, while the rest of the system experiences shorter waits.

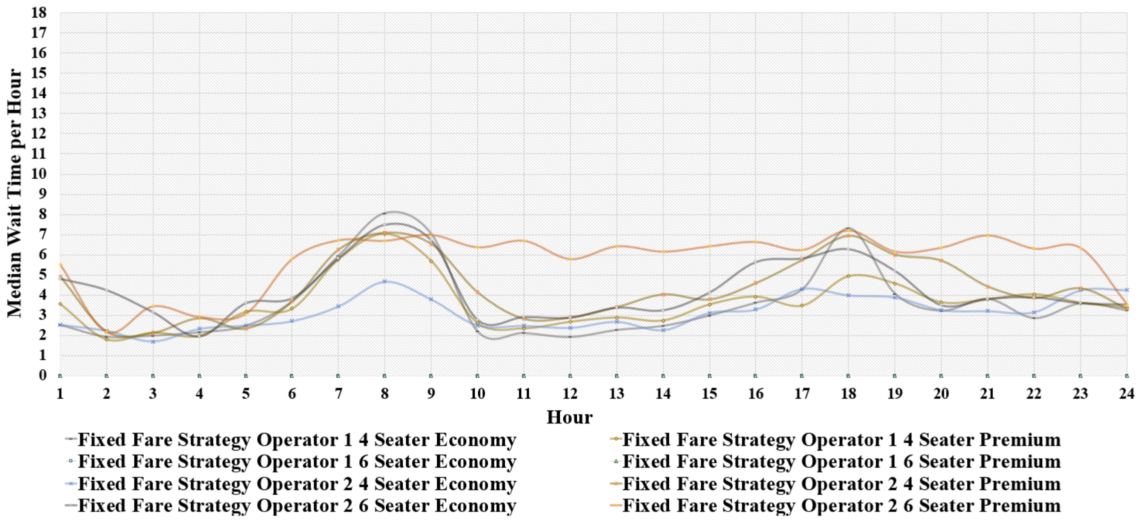


**Figure 3 Hourly Median Wait Times for SAV Services under Fixed-Fare Rules**

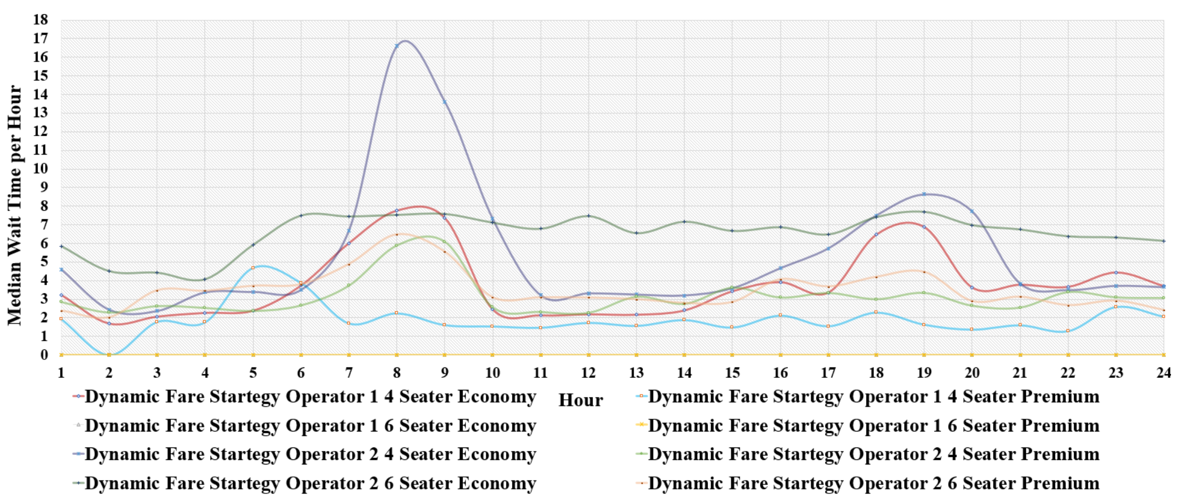


**Figure 4 Hourly Median Wait Times for SAV Services under Variable Fare Pricing**

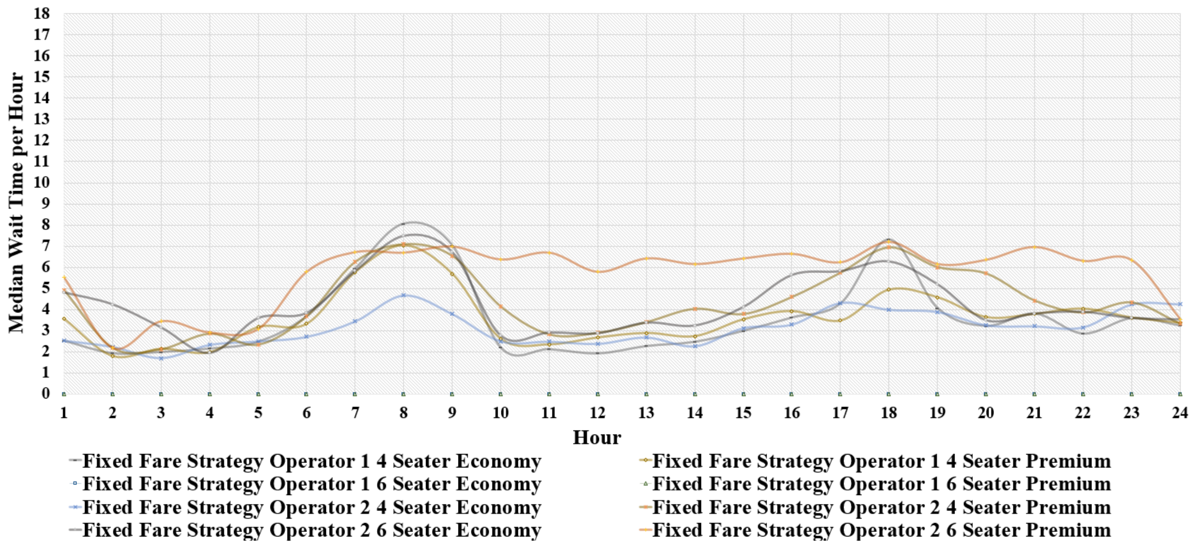


**Figure 5 Hourly Median Wait Times for SAV Services under Fixed-Fare Rules**

***Temporal Patterns in Demand by Ride Type under Fixed and Variable Fare Strategies***

Figure 6 illustrates how hourly demand varies across 24 hours under variable and fixed fare strategies for both operators' 4-seater economy and premium services. During the pre-dawn hours (1–5 AM), demand remains minimal across all services, ranging from 10 to 50 rides per hour, with variable fare strategies for both operators' economy services showing slightly higher baseline demand than their fixed-fare counterparts. As the morning commute approaches (6–8 AM), all services experience dramatic increases, but variable fare strategies demonstrate the most pronounced surges. Operator 1's 4-seater economy service under variable pricing peaks most sharply at approximately 850 rides per hour around 7 AM, while Operator 2's 4-seater economy service reaches nearly 800 rides per hour at the same time. In contrast, fixed fare strategies show more modest peaks, with Operator 1's 4-seater economy climbing to roughly 500 rides per hour and Operator 2's reaching approximately 350 rides per hour. Premium services under both fare strategies remain consistently low throughout this period, maintaining demand levels below 100 rides per hour. Following the morning surge, demand patterns reveal distinct differences between fare strategies during the midday period (9 AM – 4 PM).

Variable-fare economy services experience a temporary dip to 350-400 rides per hour before maintaining elevated plateaus of 400-450 rides per hour, while fixed fare services drop more significantly to 100-200 rides per hour. Premium services across both operators and fare strategies remain relatively flat at 10-50 rides per hour throughout the midday hours. A secondary, more substantial evening surge emerges (5–9 PM), when variable fare strategies again demonstrate superior performance1. Operator 1's 4-seater economy service returns to peaks of approximately 850 rides per hour around 7 PM, while Operator 2's 4-seater economy reaches 800 rides per hour. Fixed fare strategies show more moderate evening peaks, with Operator 1 achieving approximately 300 rides per hour and Operator 2 reaching 250 rides per hour. Premium services maintain a consistently low demand profile throughout the evening hours, rarely exceeding 50 rides per hour, regardless of the fare strategy. After 10 PM, all services gradually decline toward their overnight baseline levels, with variable-fare economy services maintaining higher residual demand than their fixed-fare counterparts through the late evening hours.

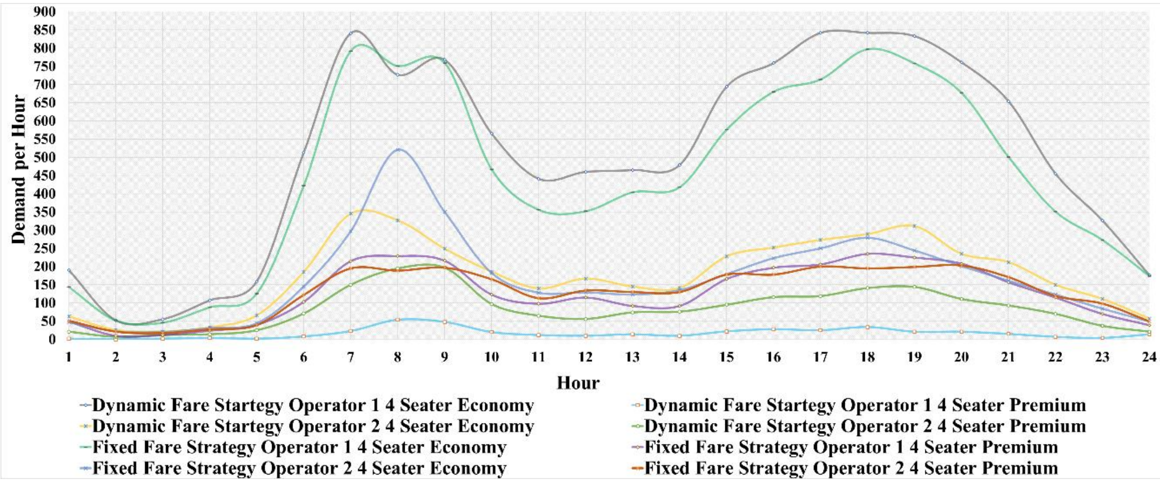


**Figure 6 Hourly Demand for 4-Seater SAVs under Fixed-Fare Rules vs Variable Fare Strategy**

The overall demand profiles revealed that variable fare strategies consistently generate 2–4 times higher total demand across all time periods, suggesting that the market shows high price elasticity. The dramatic peaks and troughs in variable fare profiles indicate that consumers are highly responsive to price signals, with variable pricing effectively capturing consumer surplus that remains untapped under fixed pricing structures. This responsiveness shows that ride-hailing demand contains significant elastic components that can be activated through strategic pricing mechanisms. Figure 7 shows hourly demand variation over a 24-hour period for 6-seater economy and premium SAVs, comparing variable and fixed fare strategies for both Operator 1 and Operator 2. During the pre-dawn hours (1–5 AM), demand across all services is low, typically ranging from 5 to 50 rides per hour. Fixed fare strategies for both operators' 6-seater economy and premium services maintain a modest baseline, with Operator 2's fixed fare economy and premium services showing slightly higher demand than their variable fare counterparts. As the morning commute (7–9 AM) approaches, all ride types of spikes: the fixed-fare 6-seat economy option peaks at nearly 180 rides per hour around 8 AM, while the fixed-fare 6-seat premium segment stays relatively flat between 110 and 125 rides per hour throughout the day (7 AM – 9 PM). Operator 1's 6-seat offerings (both economy and premium) receive virtually no demand and remain idle. When variable fares were applied, Operator 2's 6-seat economy profile follows the similar pattern but at lower volumes: the morning peak softens to about 125 rides per hour at 8 AM, then settles into a 50-ride-per-hour plateau from 10 AM to 2 PM before climbing to roughly 100 rides per hour around 7 PM and tapering off toward midnight. In contrast, the variable-fare 6-seat premium service maintains a steady demand of approximately 75 rides per hour from 6 AM to 11 PM, indicating that premium riders are less price-sensitive under the variable fare strategy.

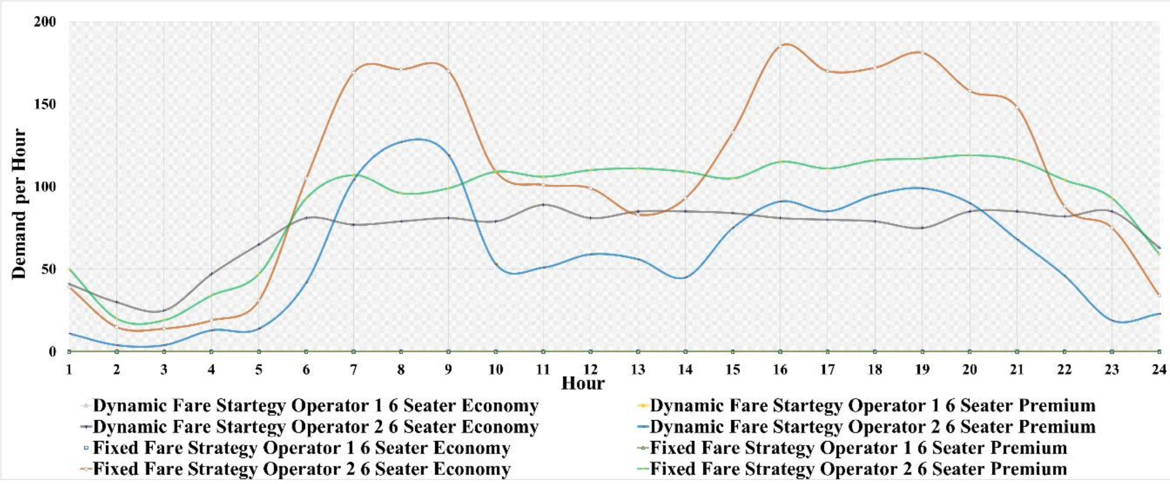


**Figure 7 Hourly Demand for 6-Seater SAVs under Fixed-Fare Rules vs Variable Fare Strategy**

## RESULTS

Tables 3 and 4 below summarize fleet performance metrics for the two-operator, multi–ride-option SAV simulation under fixed (time-invariant) pricing rules and under a variable fare strategy, where each provider's regression-based pricing algorithm continuously recalibrates fares based on real-time and lagged demand conditions.

### SAV Operational Performance Under Fixed Fares

Under fixed fares, Operator 1 charges a base fare of $2.00 plus $0.40 per mile and $0.10 per minute for its 4-seater standard SAV, $3.00 plus $0.50 per mile and $0.30 per minute for the 6-seater standard ride, $4.00 plus $0.80 per mile and $0.20 per minute for the 4-seater luxury option, and $6.00 plus $1.00 per mile and $0.40 per minute for the 6-seater luxury ride. Operator 2's fixed fare schedule comprises a base fare of $1.00 plus $0.20 per mile and $0.10 per minute for the 4-seater standard option, $1.50 plus $0.30 per mile and $0.20 per minute for the 6-seater standard option, $2.00 plus $0.40 per mile and $0.20 per minute for the 4-seater luxury option, and $3.00 plus $0.60 per mile and $0.40 per minute for the 6-seater luxury SAV. In contrast, under the variable fare strategy scenario, each operator's regression-based pricing model (shown in Table 2) determines fares endogenously as a function of trip distance, duration, instantaneous demand, past demand ratios, and the hour of day.

Under fixed-fare pricing, Operator 1 did not receive any demand (see Table 3) for 6-seaters; hence, its fleet of 245 SAVs is overwhelmingly devoted to 4-seater rides (179 SAVs), with 97% of vehicles assigned to 4-seater class and only 2% (7 SAVs) set aside for 6-seater rides. Of 238, 4-seater SAVs, 75% (approximately 179 SAVs) cater to economy riders, while the remaining 25% (about 59) operate as 4-seater luxury SAVs. A relatively smaller 6-seater SAVs, comprising six economy SAVs (86% of the XL sub-fleet) and one 6-seater luxury SAV (15% of 7), sees no demand under fixed fares and thus produces zero revenue. Operator 2, in contrast, maintains its 210-vehicle fleet more evenly across SAV sizes: 66% (approximately 139) are 4-seaters (split 68% economy, 32% luxury) and 34% (around 71 SAVs) are 6-seaters (also split 64% economy, 36% luxury). This distribution enabled Operator 2 to maintain viable service offerings in all four ride-option tiers once fixed fares are imposed. Operator 1 captured nearly 66% all 4-seater demand under the fixed-fare regime. The 165 four-seater economy vehicles collectively serve about 10,678 rides each day, yielding an average wait time of 7.6 minutes and a mean trip distance of 4.5 miles. Those 165 economy SAVs accumulate 331 miles of vehicle-miles traveled (VMT) per vehicle per day, of which 29% is empty (deadheading), and average 59.6 trips per SAV, leaving roughly 14 hours of idle time per day. The four-seater luxury arm (41 vehicles) serves 3,036 daily rides, with passengers waiting 5.5 minutes on average and traveling 3.7 miles per trip; those SAVs record 306 miles of daily VMT per vehicle (35% empty) and average 51.4 trips per day, with about 14.8 hours of idle time. Since Operator 2's fixed fares for 6-seater options are lower, all 6-seater demand is captured by Operator 2. As a result, Operator 1's 6-seater economy and luxury vehicles see zero assignments.

Operator 2's diversified fleet, in contrast, serves a mix of 4-seater and 6-seater demands under fixed fares. Its 88 4-seater economy vehicles serve 3,967 rides per day, producing a shorter average wait time of 4.9 minutes and 4.38 miles traveled per trip. Each 4-seater economy SAV covers on average 207 miles per day (28% empty) and averages 42.2 trips, experiencing about 17 hours of idle time daily. The 59 4-seater luxury vehicles, facing slightly lower demand relative to economy SAVs, served 3,120 rides per day, with an average wait of 6.5 minutes and 3.50 miles per trip; they logged 421 miles of VMT daily per vehicle and completed 69 trips per day, idle for about 11.4 hours. In the 6-seater economy tier, 38 SAVs completed 2,562 rides daily, with a 6.4 minute wait, a trip distance of 3.98 miles, 369 miles of VMT per vehicle (39%), 57 trips per day, and 12.9 hours idle. These usage patterns translate directly into each operator's cost, revenue, and profit performance under fixed fares. Operator 1's 4-seater economy SAVs incur roughly $351 in daily operating cost per vehicle (which includes owning, operating and cleaning costs) and generate $593 per SAV in daily revenue. While a 4-seater luxury yielded $62 per day per SAV. Operator 2's 4-seater economy ride offering is its most lucrative: SAVs cost roughly $249 per day and earn $371 in daily revenue, yielding $121 per SAV per day. The 4-seater luxury SAVs, however, incur $625 per day in operating costs but cannot keep up with operating outlays, so each luxury SAV loses $66 per day. In a 6-seater economy service, each of the 38 SAVs costs $452 per day and brings in $478, for a $26 daily profit. In contrast, the 6-seater luxury SAVs, despite serving 83 trips and 567 miles per day, incur $1,050 in daily costs but only earn $772, resulting in a $278 loss per SAV each day.

**Table 3 Fleet Performance Metrics for the Region of Bloomington City with Service Choices, DRS under Fixed Fares**

<table>
<tr><th></th><th colspan="4">Operator 1</th><th colspan="4">Operator 2</th></tr>
<tr><td></td><td colspan="2">4-seater (standard size)</td><td colspan="2">6-seater (XL)</td><td colspan="2">4-seater</td><td colspan="2">6-seater</td></tr>
<tr><td></td><td>Economy</td><td>Lux</td><td>Eco</td><td>Lux</td><td>Economy</td><td>Lux</td><td>Eco</td><td>Lux</td></tr>
<tr><td>SAV fleet size<br>(25% population)</td><td colspan="4">245 SAVs</td><td colspan="4">210 SAVs</td></tr>
<tr><td>Population per SAV</td><td colspan="4">167 Persons /SAV</td><td colspan="4">195 Persons /SAV</td></tr>
<tr><td>25% Demand (# Requests)</td><td colspan="4">13,714 rides per day</td><td colspan="4">11,814 rides per day</td></tr>
<tr><td>SAVs per service type (%)</td><td>179 SAVs</td><td>59</td><td>6</td><td>1</td><td>94 SAVs</td><td>45</td><td>45</td><td>26</td></tr>
</table>

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| # Served rides/day | 10,678 rides | 3,036 | - | - | 3,967 | 3,120 | 2,562 | 2,165 |
| Peak hour median wait time (min) | 7.6 min | 5.5 | - | - | 4.9 | 6.5 | 6.4 | 6.7 |
| Average travel distance/SAV rider (miles/day) | 4.5 miles | 3.7 | - | - | 4.38 | 3.50 | 3.98 | 3.63 |
| Average VMT/SAV (miles/SAV/day) | 331 mi/day | 306 | - | - | 207 | 421 | 369 | 567 |
| % empty VMT | 29% empty | 35% | - | - | 28% | 42% | 39% | 47% |
| SAV trips/SAV/day | 59.6 trips | 51.4 | - | - | 42.2 | 69 | 57 | 83 |
| Idle time (hours /SAV/day) | 14 hours | 14.8 | - | - | 17 | 11.4 | 12.9 | 7.1 |
| AVO (per revenue-mile) | 1.19 pax per revenue-mile | 1 | - | - | 1.32 | 1 | 1 | 1 |
| AVO (per revenue-min) | 1.16 pax per revenue-min | 1 | - | - | 1.25 | 1 | 1 | 1 |
| Cost per SAV ($/SAV/day) | $351/SAV/day | 479 | 60 | 120 | $249 | 625 | 452 | 1050 |
| Revenue per SAV ($/SAV/day) | $593/SAV/day | 541 | 0 | 0 | $371 | 559 | 478 | 772 |
| Profit per SAV ($/SAV/day) | $59/SAV/day | 62 | -60 | -120 | $121 | -66 | 26 | -278 |

**SAV Operational Performance under Variable Fares**

With 245 SAVs and variable pricing, Operator 1 serves nearly all 4-seater economy requests (12,164 rides per day) under 25% fixed demand (see Table 4). Each 4-seater economy SAV averages a 7.7-minute passenger wait and a 4.6-mile per trip, which translates to 389 miles of VMT per vehicle per day (30% empty) and 67.9 trips per SAV, leaving roughly 12 hours idle each day. Because regression-based fares rise during peak demand, these SAVs generated $786 in daily revenue against $399 in operating costs (ownership, per-mile, and cleaning), yielding $386 profit per SAV per day. Operator 1's 4-seater luxury vehicles, however, receive only 400 ride requests, resulting in a 2.2-minute wait and just 0.78 miles per trip on average. Since each luxury SAV still incurs 11.5 miles of VMT per day (43% empty) but completes only 6.7 trips, its operating cost is $109 while revenue is only $47 per vehicle per day, resulting in a $62 daily loss per 4-seater luxury SAV. The six-seater vehicles see no demand at all, producing no revenue (and therefore carry their full ownership and cleaning cost of $60 or $120 per day as a loss of $60 or $120 per SAV). Operator 2's 4-seater economy SAVs collectively saw demand of 4,213 rides per day, with passenger waiting an average of 15.7 minutes and traveling 5.9 miles. Those SAVs logged 439 miles of VMT per day (26% empty) across 78 trips, leaving 11.1 hours idle. Under variable fares, each SAV in this tier earned $1,252 per day while costing $449 to operate, resulting in a $793 profit per SAV per day. The 4-seater luxury SAVs served 2,007 rides, with passengers waiting 4.8 minutes on average and traveling 2.47 miles per trip. In the 6-seater economy tier, 20 SAVs serve 1,744 rides per day with a 7.2-minute passenger wait time and 4 miles per trip.

**Table 4 Fleet Performance Metrics for the Region of Bloomington City with Service Choices, DRS under Variable Fares**

| | Operator 1 | | | | Operator 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | 4-seater (standard size) | | 6-seater (XL) | | 4-seater | | 6-seater | |
| | Economy | Lux | Eco | Lux | Eco | Lux | Eco | Lux |
| SAV fleet size (25% population) | 245 SAVs | | | | 140 SAVs | | | |
| Population per SAV | 144 Persons /SAV | | | | 252 Persons /SAV | | | |
| 25% Demand (# Requests) | 12,564 rides per day | | | | 9,357 rides per day | | | |
| SAVs per service type (%) | 179 SAVs | 59 | 6 | 1 | 54 | 41 | 20 | 25 |
| # Served rides | 12,164 rides | 400 | - | - | 4,213 | 2,007 | 1,744 | 1,393 |
| Peak hour median wait time (min) | 7.7 min | 2.2 | | | 15.7 | 4.8 | 7.2 | 5.2 |
| Average travel distance/SAV rider (miles) | 4.6 miles | 0.78 | - | - | 5.9 | 2.47 | 4.12 | 2.42 |
| Average VMT/SAV (miles/day) | 389 mi/day | 11.5 | - | - | 439 | 212 | 664 | 250 |
| % empty VMT | 30% empty | 43% | - | - | 26% | 33% | 36% | 46% |
| SAV trips/SAV/day | 67.9 trips | 6.7 | - | - | 78 | 49 | 87.2 | 55.7 |
| Idle time/day (hours /SAV/day) | 12 hours | 21 | - | - | 11 | 17.5 | 4.6 | 16.4 |
| AVO (per revenue-mile) | 1.18 pax per revenue-mile | 1 | - | - | 1.55 | 1 | 1 | 1 |
| AVO (per revenue-min) | 1.15 pax per revenue-min | 1 | - | - | 1.45 | 1 | 1 | 1 |
| Cost per SAV ($/SAV/day) | $399/SAV/day | 109 | 60 | 120 | $449 | 396 | 720 | 587 |
| Revenue per SAV ($/SAV/day) | $786/SAV/day | 47 | 0 | 0 | $1252 | 576 | 1266 | 902 |
| Profit per SAV ($/SAV/day) | $386/SAV/day | -62 | -60 | -120 | $793 | 180 | 547 | 314 |

**Economic Comparison**

When fares remain fixed, Operator 1's strategy of concentrating almost entirely on 4-seater service yields a 51% margin overall (Table 11) driven by modestly profitable 4-seater economy and luxury SAVs, while its small 6-seater arm sits idle. 4-seater economy SAVs earn $593 per day and net $59 per day after operating costs, while 4-seater luxury SAVs earn $541 and net $62. Because the 6-seater economy and luxury tiers receive no demand, since their posted prices are too high relative to riders' willingness to pay, they generate zero revenue and run losses of $60 and $120 per SAV per day, respectively. In contrast, Operator 2's mixed-fleet strategy under fixed fares yields just a 2% overall margin. Although 4-seater economy remains profitable, both 4-seater luxury and 6-seater luxury SAVs incur steep losses that significantly outweigh the gains from 4-seater and 6-seater economy, owing to their high operating costs. Thus, with static pricing, Operator 1 succeeds by cutting its 6-seater fleet to avoid losses, while Operator 2 loses money in its higher-cost segments because those tiers cannot attract enough riders to cover operating expenses. Under variable fares, regression-based pricing changes the economic performance dramatically for both operators. Operator 1's 4-seater economy SAVs now earn far more per day—turning a $386 profit per SAV. Even after "losing" money on a handful of 4-seater luxury vehicles (which now receive few ride requests), its overall margin climbs to 83%. However, its 6-seater vehicles remain unused even under variable fares. In contrast, Operator 2's variable fares transform every tier into a profitable ride offering: 4-seater economy SAVs earn $793 in daily profit per SAV, 4-seater luxury SAVs net $180, 6-seater economy SAVs net $547, and 6-seater luxury SAVs net $314. As a result, Operator 2's overall margin rises to 99%, eliminating the losses it suffered under fixed fares.

**Table 5 Revenue and Profit per SAV for Operators 1 and 2 under Fixed vs. Variable Fare Regimes**

| | | Operator 1 | | | | Operator 2 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | 4-seater (standard size) | | 6-seater (XL) | | 4-seater | | 6-seater | |
| | | Eco | Lux | Eco | Lux | Eco | Lux | Eco | Lux |
| Fixed Fares | Revenue per SAV ($/SAV/day) | $593 | $541 | $0 | $0 | $371 | $559 | $478 | $772 |
| | Profit per SAV ($/SAV/day) | $59 | $62 | -$60 | -120 | $121 | -$66 | $26 | -$278 |
| | %Profit across Service | 51% ($189/SAV/Day) | | | | 2% ($11.5/SAV/Day) | | | |
| Variable Fares | Revenue per SAV ($/SAV/day) | $786 | $47 | $0 | $0 | $1,252 | $576 | $1,266 | $902 |
| | Profit per SAV ($/SAV/day) | $386 | -$62 | -$60 | -$120 | $793 | $180 | $547 | $314 |
| | %Profit across Service | 83% ($265/SAV/day) | | | | 99% ($492/SAV/day) | | | |

## CONCLUSIONS

This study demonstrates that incorporating regression-based, ride-option–specific pricing into a multi-operator SAV simulation addresses the limitations of static-multiplier approaches. By calibrating each operator's fare models using NYC TLC data and allowing hourly adjustments in response to real-time demand, competitor pricing, and historical spillovers, the study revealed how profit-maximizing algorithms rebalance service tiers, an effect that fixed fares are unable to capture. With variable pricing in place, economy rides get squeezed into a very sharp morning bottleneck, Operator 2's 4-seat economy riders wait almost 17 minutes at 8 AM, compared to under 5 minutes with flat fares, yet those same riders wait just 1.5–3 minutes during midday and off-peak hours. Premium and larger-seat services also see their waits shrink to that 1.5–3 minute window. By contrast, keeping fares fixed yields more even peaks, approximately 7–8 minutes for all services at rush hour, and a steady wait of 2–3 minutes throughout the day. Variable pricing also magnified economy-tier demand by roughly 2-3 times at rush hours, peaking at 800–850 rides/hour versus 350–500 under fixed fares, and raises the midday plateau to 400–450 rides/hour (compared with 100–200). In contrast, fixed fares showed moderate variation in their demand, with economy demand peaking at 350–500 rides/hour in the morning and evening and dipping to 10–50 rides/hour pre-dawn. Premium segments remain underused (<100 rides/hour) under both regimes. By raising economy fares during surges and simultaneously narrowing premium surcharges when demand eases, variable pricing halves the morning and evening peaks for 4-seat economy trips and makes premium rides comparatively more attractive, driving premium volumes to more than double under surge conditions. During non-peak times, variable pricing attracted a consistent level of trip demand across SAV types, contrasting with the dramatic troughs and peaks resulted from the fixed fare regime. In effect, adaptive pricing not only tempers extreme surges but also shifts riders toward higher-yield options, resulting in a smoother and more balanced utilization profile throughout the day. Fixed-fare rules also forced every operator to decide which ride type it can profitably field at posted prices. Operator 1, for example, allocates almost its entire fleet to 4-seater rides because fixed XL fares fail to cover the higher operating costs, those SAVs simply sit idle and lose money. Operator 2, by contrast, maintained a mixed fleet of both 4 and 6-seater vehicles, betting that there will be enough riders willing to pay fixed premium and XL fares to cover the high per-mile and cleaning costs.

In practice, however, Operator 2's 4-seater premium and 6-seater premium SAVs operate at a loss (\$66 and \$278 per day) because the static fare schedule is too high relative to riders' willingness to pay: these vehicles never attract enough trips to break even. Meanwhile, its 4-seater economy and 6-seater economy SAVs manage only modest profits (\$121 and \$26 per day), which barely offset the losses in the premium tiers and produce an overall margin of just 2%. Once simulation is switched to a variable-fare strategy, the entire profitability landscape shifts because the system can raise or lower per-ride prices in response to real-time demand conditions. In every economy tier (both 4 and 6-seater), variable pricing unlocks large surge premiums during peak hours. For Operator 1, 4-seater economy profit jumps from \$59 to \$386 per SAV per day. Though running costs rise by nearly \$50, the ability to charge surge-adjusted fares during rush demands yields a sixfold increase in net profit. Operator 2's 4-seater economy SAVs fare even better, with profits per SAV-day leaping from \$121 to \$793! The same increases hold for 6-seater economy under Operator 2: fixed pricing produces only \$26 per-SAV-day profit, but variable pricing pushes that to \$547. As long as sufficient riders book during peak times, the higher surge fares for economy rides outweigh the extra mileage and cleaning expenses, turning a slim profit into a substantial one. In the premium tiers, variable pricing can have one of two effects, depending on whether an operator successfully targets truly price-insensitive riders. Operator 2's 4-seater premium service, which lost \$66 per SAV per day under fixed fares, results in an overall profit under variable pricing: its cost per SAV-day falls from \$625 to \$396 (because few of those vehicles run outside peak windows), and its revenue per SAV increases modestly from \$559 to \$576. As a result, 4-seater premium flips from a loss to a \$180 daily profit (per SAV).

Similarly, Operator 2's 6-seater premium vehicles move from a fixed-fare loss of \$278 per day to a \$314 daily profit (per SAV-day) under variable fares. However, because an operator's fleet is based on anticipated demand, aiming to minimize both empty VMT and idle time, the premium tiers under variable pricing become heavily undersized and unprofitable. Fixed- and variable-pricing strategies have differing outcomes for operators. First, in a fixed-fare environment, operators must "pick winners" ahead of time: Operator 1's 6-seaters had to be abandoned and focussed on 4-seaters to protect its margins, while Operator 2's distributed demand across its diverse fleet ended up losing money in its high-cost premium segments. Second, variable fares transform every tier that can capture a willingness-to-pay spike into a profit center, regardless of how unprofitable that same tier appeared under fixed fares. When a tier truly cannot attract riders at any price (as in Operator 1's 6-seaters), those vehicles simply sit idle, halting incremental losses rather than compounding them.

The operational and financial bottom line of this strategic shift is quite clear. Across the entire Bloomington network, the variable fare strategy drove significant gains in operational efficiency: while overall demand was reduced by 14%, total VMT fell by 17%, with eVMT declining even more sharply by 21%. This improved efficiency had a significant financial payoff, yielding a 174% boost in total profit and raising the average daily profit per SAV from $107 to $348. These impacts of variable pricing were also driven by better SAV usage, especially for Operator 2 with a diversified fleet. While Operator 1's already focussed 4-seater fleet saw little change in its occupancy rates, Operator 2's performance saw significant boost. Its average vehicle occupancy rose 19% per revenue-minute (from 1.32 to 1.55 persons), while occupancy per revenue-mile rose 16% (from 1.25 to 1.45 persons), confirming that variable pricing successfully turned its underused premium and XL vehicles into efficiently dispatched, profitable assets. These findings carry significant policy and operational implications and can help regulators to recognize that simplistic fare caps or surge multipliers risk starving SAV fleets of revenue and forcing some ride options withdrawals. Instead, policies should promote data-driven pricing frameworks that align operator profitability while minimizing empty VMT. SAV operators should also tailor their fleet compositions to both local demand patterns and the competitive landscape. As the analyses showed, while economy-focused fleets can excel in low-demand areas, mixed fleets paired with variable pricing can capture broader market segments without sacrificing margins.

## LIMITATIONS AND FUTURE SCOPE

While this study examines a focused window in which two SAV fleets compete, several key assumptions cause the modeled scenarios to differ in many ways from real markets. For example, these simulations exclude vehicle downtime for refueling, charging, routine cleaning, and maintenance, factors that, in practice, reduce fleet availability and generate added empty miles, thereby overestimating operational efficiency. The competitive framework assumes the simultaneous presence of two operators, each maintaining a full portfolio of four distinct service options throughout the simulation period. In reality, SAV markets are experiencing sequential operator entry where leading operators like Waymo currently dominate with little immediate competition, while emerging operators (e.g., Zoox and Tesla) enter progressively over time. Such staggered entry will affect customer loyalty formation, pricing leverage, and ongoing viability of various service options. The variable pricing models implemented assume that each operator adjusts fares independently, without anticipating or strategically responding to competitors' fares.

In practice, ride-hailing market competitors continuously track and respond to one another's fare changes through sophisticated competitive fare adjustment algorithms. As a result, real-world outcomes may result in optimistic projections of profits as fare undercutting, or dynamic "fare wars" are not explicitly simulated. Moreover, this study holds SAV fleet sizes constant across the day and uses different pricing strategies to allocate scarce capacity, yielding pronounced peak waits for economy riders. In contrast, traditional TNCs expand human-driver supply during peaks, mitigating wait spikes without relying exclusively on higher prices. A hybrid design such as, baseline SAV capacity complemented by flexible human-driven supply during peaks and special events, could further reduce peak waits and price volatility. Future extensions can include simulating such mixed fleets, as well as policies that promote all-day pooling and intercity repositioning of SAVs during major events. Over a longer horizon, restrictions on human-driven trips in sensitive zones (e.g., CBDs) could further shift the balance toward pooled SAV services.

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## AUTHOR CONTRIBUTIONS

The authors confirm the contribution to the paper as follows: Conceptualization, data curation, formal analysis, investigation and methodology: Priyanka, P.; Jayashankar, N; Gurumurthy, K.M; and Kockelman, K.; Project administration and Supervision: Kockelman, K. and Gurumurthy, K.M; Visualization and Writing – original draft: Priyanka, P., Kockelman, K.; Writing – review & editing: Kockelman, K. and Gurumurthy, K.M; The authors confirm their respective contributions to this manuscript as outlined above. We acknowledge and thank Helena Chandy for her review and valuable feedback.

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